Neural recognition and postdiction by temporal distributed distributional code

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Model

- Internal model: latent \( p(z_t|x_{t-1}) \) and observation \( p(x_t|z_t) \)
- DDC: encode \( q(z_t|x_{t-1}, z_{t-1}) \) by \( r_t := \mathbb{E}_q[\psi(y(z_{t-1})] \)
- Temporal code: \( \psi_t = k(\psi_t, z_t) \)
- Sleep phase: train \( h(r_{t-1}, x_t) \) by MSE (\( \delta \)-rule)
- Wake phase: predict \( \mathbb{E}_q[\psi_t] \approx r_t = h(r_{t-1}, x_t) \)
- Flexible \( q \) (non-Gaussian), neural (\( \delta \)-rule), postdictive

Key results

- Bimodal filtering
  - Exact posterior (bootstrap particle filter)
  - True \( z \)
  - Bilinear \( h \) DDC filter
  - Linear \( h \) DDC filter

Auditory continuity illusion

Postdictive filtering

- At each time \( t \), have:
  - \( r_{t-1}, z_{t-1}, \psi_t \)
  - Sample \( z_t, x_t \sim p \)
  - Compute \( \psi(t) = k(\psi(t), z_t) \)
  - Update \( W \) to minimise:
    \( \| h_W(r_{t-1}, x_{t}) - \psi(t) \|^2 \) (\( \delta \)-rule if \( h \) is linear/bilinear filter)
  - Readout: find \( \mathbb{E}_q[\psi(t)|z(t)] \)

Network activation during stimulus B

Compare with monkey A1 neurons [5]

Reference

- A single summary statistics of \( z_{t-1}, x_{t-1} \)
- \( \psi_t = U\psi_t + \gamma(z_t) \) random but fixed temporal encoding function
- \( h_W(r_{t-1}, x_{t}) \) or \( h_W(r_{t-1}, x_{t}) \) random but fixed
- Possible to assume \( h \) is linear only in \( \sigma(x_t) \) and derive a formal solution, albeit with complicated neural implementation
- If the state-space model is stationary, \( W \) should converge
- Independent noise in \( \psi_t, \sigma_t \) average out for large population
- Adaptation: follow gradient of variational objective \( \nabla_{\theta} T(\bar{z}, x) \)

Learning to infer

- At each time \( t \), have:
  - \( r_{t-1}, z_{t-1}, \psi_t \)
  - Sample \( z_t, x_t \sim p \)
  - Compute \( \psi(t) = k(\psi(t), z_t) \)
  - Update \( W \) to minimise:
    \( \| h_W(r_{t-1}, x_{t}) - \psi(t) \|^2 \) (\( \delta \)-rule if \( h \) is linear/bilinear filter)
  - Readout: find \( \mathbb{E}_q[\psi(t)|z(t)] \)

DDC: encode \( q(z_{t-1}|x_{t-1}) \) by \( r_t := \mathbb{E}_q[\psi(y(z_{t-1}))] \)

Inferential model

- No assumptions on \( z \)
- Internal (generative) vs inferential (\( \delta \)-rule)
- \( \psi_t = k(\psi_t, z_t) \)
- \( \psi(t) \) is arbitrary \( q(\psi(t)|z(t)) \)
- \( h_W(r_{t-1}, x_{t}) \) outputs \( \bar{z}_{t}(t) \)
- Assess by max ent

Model details

In sleep phase, model solves
\[
\min_W \mathbb{E}_{p(z_{t-1})} \left[ \| h_W(r_{t-1}, x_{t}) - \psi(t) \|^2 \right] \tag{1}
\]

- \( \mathbf{r}_t \) is a summary statistics of \( x_{t-1}, z_{t-1} \)
- \( \psi(t) = U\psi_t + \gamma(z_t) \) random but fixed temporal encoding function
- \( h_W(r_{t-1}, x_{t}) \) or \( h_W(r_{t-1}, x_{t}) \) random but fixed
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Additional results

Occluded tracking with noisy DDC